Environmental Modelling & Software 101 (2018) 204–217

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Municipal water planning and management with an end-use based simulation model

Kai Wang, Evan G.R. Davies*

Department of Civil and Environmental Engineering, University of Alberta, 9211 – 116 St NW, Edmonton, Alberta, T6G 1H9, Canada

A R T I C L E I N F O

Article history:
Received 17 May 2017
Received in revised form
13 October 2017
Accepted 26 December 2017
Available online 6 January 2018

Keywords:
Water demand model
Municipal water conservation
Decision-support tool
Scenario analysis
System dynamics
Calgary

A B S T R A C T

This study introduces an end-use-based system dynamics model to support municipal water planning and management over the medium-to long-term. The Calgary Water Management Model (CWMM) simulates water demand and use to 2040 at a weekly time step for ten municipal end-uses, as well as the effects of population growth, climate change, and various water management policies, and includes policy implementation costs for assessment of conservation versus economic trade-offs. The model was validated against historical water demand data for Calgary, Alberta. A series of scenario simulations showed (1) potentially large changes to both seasonal and non-seasonal water demands with climate change and population growth, (2) a need to enhance historical water management policies with new policies such as xeriscaping and greywater reuse to achieve water management goals, and (3) the value of an end-use based model in simulating management policy effects on municipal water demand and use.

Software availability

Software name: CWMM (Calgary Water Management Model)
Developers: K. Wang and E. Davies, University of Alberta
Year first available: 2017
Program language: Vensim
Hardware requirements: No special requirements
Software required: Vensim Model Reader, Ventana Systems Inc.
Availability and cost: Please contact the corresponding author for a free copy

1. Introduction

Population growth and climate change present challenges for water resources planners and managers (McDonald et al., 2011), and water security is increasingly of concern to urban authorities (Grafton et al., 2011; Yigzaw and Hossain, 2016). On the water supply side, a variety of studies have investigated effects of changing precipitation patterns, glacial retreat, and sea level rise on hydrological variables (cf. Dibike et al., 2016; Eshtawi et al., 2016; Scalzitti et al., 2016) as well as urban hydraulic infrastructure expansions and management (Padowski and Jawitz, 2012; Mays, 2002). Water authorities also recognize the value of managing water demand – the focus of this research – which is less time-intensive and more cost-effective and environmentally-friendly than supply-side management (House-Peters and Chang, 2011; Gleick, 2003).

Municipal water systems serve residential, industrial, commercial, institutional and public clients (Mayer et al., 1999), whose demands are affected by both long-term impact factors – population change, economic conditions, and water conservation activities – and short-term impact factors, including seasonal weather patterns and the associated summer peak demands (March and Saurí, 2009). In most urban systems of North America, the total water demand increases with population growth, while per capita water use decreases with water conservation efforts such as adoptions of “low-flow” fixtures and appliances, educational campaigns, water metering and consumption feedback, leak detection programs, economic incentives, xeriscaping, and water treatment and reuse (Billings and Jones, 2008; Sønderlund et al., 2016; DeOreo et al., 2016).

Reliable water demand modeling and forecasting provides the basis for both the short-term (operational) and long-term (planning) aspects of urban water management, in terms of capital investment, infrastructure expansion, conflict mitigation, policy analysis, and system optimization, and it can improve

* Corresponding author.
E-mail address: evan.davies@ualberta.ca (E.G.R. Davies).

https://doi.org/10.1016/j.envsoft.2017.12.024
1364-8152/

understanding of the underlying factors and dynamics that affect water demand and use (Billings and Jones, 2008). However, accurate demand forecasting and analysis are challenging because of, (1) the limited quantity and quality of data (Brown, 2002), (2) the numerous variables and drivers that affect demand (March and Saurí, 2009), (3) the high uncertainties associated with climate change, economic conditions, population growth, and conservation activities (Gober et al., 2011), (4) the complexity of a quantitative analysis of water conservation options and their implementation costs (Billings and Jones, 2008), and (5) the different model horizons required for short-term and long-term purposes, both of which affect water security (Donkor et al., 2014).

This paper presents a novel end-use-based model as a decision-support tool for municipal water management that addresses many of the challenges above. Intended for tactical (1–10 years) and strategic (long-term) use (see Table 1 in Donkor et al., 2014), the model simulates short- (weekly) and long-term (>10 years) municipal water demand and use patterns under various climate change, population growth, and water conservation scenarios, and reveals management trade-offs such as the potential water savings and economic costs of alternative water management policies. It includes ten specific end-uses with seven residential end-uses (six indoor and one outdoor use), and three non-residential uses, and simulates per capita water demand based on the number of water fixture uses per day and their associated water requirements, which are affected by water conservation policies, as well as appliance and fixture characteristics. Called the Calgary Water Management Model, or CWMM, the model runs fast (a single simulation on a Windows desktop takes a fraction of a second), is easy to use, requires relatively few input data, and matches the historical municipal demands in Calgary, Alberta, while also permitting exploration of various plausible water scenarios into the future. A system dynamics model, CWMM can be adapted to other municipalities by changing model inputs stored in a MS Excel file, and refined from a whole-city scale to represent individual neighborhoods or city regions.

The paper is structured as follows. First, municipal water modeling methodologies and models are reviewed. Then the research area and data availability are presented in terms of water supply, demand, and management conditions. The model is next described and validated using data for Calgary, and sample results such as per capita water demand, management policy conservation effectiveness, and policy cost are presented. Finally, the paper closes with conclusions, a discussion of model limitations, and potential next steps for the research.

2. Municipal water management and modeling

A wide range of methods can be used for municipal water management and modeling, with the selection depending on modeler skill, available resources and data, and accuracy requirements. Methods such as time-series analysis, regression analysis, stochastic modeling, artificial intelligence (AI), and system dynamics (SD) are discussed in this section, as well as modeling concerns related to water customer disaggregation, modeling time step, economic considerations, and climate change. Note that many of these methods, such as time-series and regression models, or artificial neural networks and regression models, are often used in combination to produce "hybrid models" that typically improve water demand forecasting performance over the use of the individual methods (Donkor et al., 2014).

2.1. Available modeling methods

Water demand projections rely on estimated population growth and per capita water demands, and modeling methods differ primarily in their treatment of the latter. Time-series models predict per capita demand based on historical trends, using moving averages, exponential smoothing, or autoregressive integrated moving-average methods (Billings and Jones, 2008), and with fine-temporal scale data can "reveal significant temporal trends in water consumption correlated with economic variables … as well as weather and climate factors" (House-Peters and Chang, 2011: 4). Regression models have also been used extensively historically (Donkor et al., 2014) and employ social and economic factors, called explanatory variables, including water price, house and lot size, water-saving technologies, family income, education, and gender to estimate per capita or family water consumption through linear, log-linear, or exponential models (Billings and Jones, 2008). These drivers are analyzed in terms of temporal and spatial scales (House-Peters and Chang, 2011), direct and indirect impacts on water demand (Jorgensen et al., 2009), and economic and non-economic factors (March and Saurí, 2009). Both approaches require typically modest computing power (House-Peters and Chang, 2011) but do not generally account for population growth or water conservation efforts; therefore, they are usually applied to short-term demand prediction (typically less than a year) for small utilities. See Qi and Chang (2011), House-Peters and Chang (2011), and Donkor et al. (2014) for examples.

Stochastic models may take several forms. Stochastic Poisson rectangular pulse (PRP) models generate rectangular pulses that represent sub-daily scale residential water demands, and are typically applied to water quality modeling in drinking-water distribution systems; they simulate pulse arrival time, intensity (flow), and duration (Creaco et al., 2017). Although such models require (expensive) flow measurements at short time intervals to determine PRP model parameters (Blokker et al., 2010), their results have been shown to closely match observed household and aggregated (21-household) water demands at short time scales of 1 s to 1 h (Creaco et al., 2017). PRP-based models can also reproduce specific residential end-uses of water (Blokker et al., 2010) and offer the potential of projecting the results of changes both in appliance efficiencies and in human behavior over the longer term (Creaco et al., 2017). Stochastic models for long term projections can be generated, for example, from Monte Carlo simulations of daily temperature and precipitation values and combined with a deterministic water demand model (Yung et al., 2011), or simpler multiple linear regression models that generate monthly demands over several decades (Haque et al., 2014).

Artificial intelligence methods include artificial neural networks (ANN), fuzzy inference systems, agent-based modeling (Qi and Chang, 2011; House-Peters and Chang, 2011), Support Vector

Table 1
Sample changes in North American municipal water use from 1999 to 2016 (DeOreo et al., 2016).

Category	Toilet	Shower	Faucet	Dishwasher	Laundry
Fixture uses per capita per day in 1999 (number)	5.05	0.66	15	0.09	0.81
Fixture uses per capita per day in 2016 (number)	5.00	0.69	20	0.10	0.78
Average per capita daily use in 1999 (lpcd)	70	44	41	3.8	57
Average per capita daily use in 2016 (lpcd)	53.8	42	42	2.6	36

Machine, Extreme Learning Machine (Mouatadid and Adamowski, 2017), and other approaches; ANN in particular has been widely used for water demand projections, typically for short-term forecasts of hours to months (Ghalehkhondabi et al., 2017; Qi and Chang, 2011). A data-driven approach, ANNs offer excellent predictive capacity, require fewer assumptions than traditional statistical models (Ghalehkhondabi et al., 2017), and can model nonlinear relationships between water demand/consumption and explanatory variables (Qi and Chang, 2011) for the projection of future demands. For example, a set of dynamic ANN models developed by Ghiassi et al. (2008) for urban water demand forecasting at daily, weekly, and monthly time scales produced accuracies above 99%, and multiple studies have concluded that ANN models outperform both multiple regression and time-series models (House-Peters and Chang, 2011). ANN models are relatively straightforward to develop and validate, often simply from historical water demands. However, their accuracy depends significantly on the quantity and quality of historical data (Billings and Jones, 2008; Ferraro and Price, 2011), as well as on the learning algorithm used to train the ANN model (House-Peters and Chang, 2011; Ghalehkhondabi et al., 2017). Further, to prepare ANN models, researchers must select appropriate input variables by "pruning" their initial selections into a final set of predictors, select among available ANN network configurations, and determine the appropriate number of hidden layers and hidden nodes in the network; they must also separate training from testing data (Yung et al., 2011). Finally, the relationships between explanatory variables and water demand – represented as coefficients in the regression equations or ANN models – are time-invariant, and are therefore less appropriate for long-term planning (Donkor et al., 2014). Such models also have limited ability to improve understanding of the components and dynamics of municipal water system or assess alternative management strategies, since the explanatory variables are not usually tied to specific water end-uses or conservation policies.

Finally, system dynamics (SD) models attempt to replicate real-world physical structures and processes – in this case, to simulate the water end-use processes that together produce the total municipal demand. System dynamics provides both conceptual and quantitative methods to represent, simulate, and aid exploration of complex feedback and non-linear interactions among system components, management actions, and performance indicators (Elsawah et al., 2017), and its "causal-descriptive" mathematical models (Barlas, 1994) explicitly model the feedback structures, stock and flow processes, and delays that characterize real-world systems (Sterman, 2000). The approach has been used widely for water resources policy assessment and decision making through alternative scenario building, sensitivity analysis, and gaming (Winz et al., 2009; Mirchi et al., 2012; Chen and Wei, 2014; Alessi and Kopainsky, 2015; Savic et al., 2016). SD models are often developed in a participatory fashion that increases the chance that model solutions will be identified and accepted (Brown et al., 2015; Inam et al., 2015), and that allows researchers, policy-makers, managers and the public to evaluate proposed management actions, identify trade-offs, and improve their understanding of system behaviour (Williams et al., 2009).

Municipal water systems have well-established "end-uses" such as toilet flushing, kitchen uses, showering, lawn watering, commercial uses, and so on, that are focuses of different demand management programs (DeOreo et al., 2016). System dynamics can model these individual end-uses through a structural approach, and its simulated end-use water demands, and their summation to total residential and commercial demands, for example, can then help managers to plan municipal systems for capacity expansions for specific water users; analyze policy, environmental, and economic trade-offs; explain root causes of system behavior; show consequences of alternative actions clearly; and potentially mitigate conflict among various end-users (Stave, 2003). Municipal water managers usually implement several policies simultaneously, making estimation of the effectiveness of individual options difficult, especially under population growth and climate change uncertainties (Tanaka et al., 2006). SD models can be used to reveal individual and combined effects of policies through scenario investigations, assess effects of new interventions and identify the end-uses with the highest consumption (Hussien et al., 2017), and test policy effects over a wide range of plausible futures through sensitivity analyses (Gober et al., 2011).

Municipal water systems also have important "cause-and-effect" interactions. For example, a water shortage in one year, with associated water rationing, could also increase water conservation efforts and thereby mitigate the impact of future shortages (Pacific Institute and NRDC, 2014). Such interactions can be investigated through the incorporation of feedback mechanisms – in which the initial "cause" produces action that ultimately reduces the effects of future "causes" – to support management and planning at the strategic level (Mirchi et al., 2012). Thus, SD models allow decision makers to investigate both changes in human behavior and technological changes in fixtures and appliances, by assembling various changes in policy and model parameters into scenarios and then comparing their results. Examples of SD applications to municipal water management include Qi and Chang (2011), Gober et al. (2011), Qaiser et al. (2011), Ahmad and Prashar (2010), and Stave (2003).

Finally, despite these advantages, it is important to note that SD models can be data-intensive when compared with the other methods above. For example, an end-use based model requires specific values for various water end-uses and for the effects of various demand management options, and its adaptation to other locations could potentially necessitate in-field data collection to establish average fixture counts and usage, outdoor use patterns, and conservation program adoption rates and effectiveness. Further, the stakeholder engagement efforts recommended in the SD literature may be time-consuming. However, once developed, an end-use based SD model has a relatively transparent structure that is easy to understand and modify, and that provides comprehensive and clear results to users and decision makers through alternative scenarios (Wang and Davies, 2015) and Monte Carlo simulations. The approach can also produce good results where data are limited: for example, CWMM performs well, as described below, using a combination of average North American municipal water use data from DeOreo et al. (2016), and location-specific data for Calgary, Alberta.

2.2. Model characteristics and capabilities

The level of model disaggregation significantly affects the abilities and accuracy of municipal water demand models (Billings and Jones, 2008), where models with more customer categories provide greater insight into sources of demands and effects of management programs, and can also help to improve model accuracy. The level of aggregation depends on utility size, modeling method, water metering characteristics, and data availability. For example, small utilities may not be able to categorize customers because of potentially excessive volatility within customer categories or inadequate data; therefore, such systems are usually modeled with time-series and regression methods (Billings and Jones, 2008). Utilities that use customer categories and collect data on water end-uses and conservation program effectiveness may be able to model specific water end-uses. Typical data collection approaches include billing data analysis, customer interviews, surveys, home

audits, retrofit studies, flow data recorders, and flow trace analysis software (DeOreo et al., 2016); for more information, see Grafton et al. (2011), Mayeret al. (1999), and DeOreo et al. (2016), who describe data collection efforts in the areas of demographics, attitudinal and consumptive behaviors, and household water end-uses (and the physical characteristics of houses and landscapes). In contrast with time-series, regression and artificial intelligence models, which usually focus on general customer categories, a variety of SD models include residential, industrial, commercial, and institutional customer categories. For example, Gober et al. (2011) simulated both residential and commercial uses, and Qaiser et al. (2011) and Stave (2003) included indoor and outdoor residential water uses. A more detailed municipal SD model, developed by Ahmad and Prashar (2010), included residential end-uses such as kitchen, toilet, bath, laundry, and outdoor uses, as well as public, commercial, and industrial uses, while Hussien et al. (2017) projected both a larger number of household water end-uses – that relied on a detailed water use survey described in Hussien et al. (2016) – as well as annual household energy and food consumption to 2050. Note that other recent studies using different methodologies have also applied a residential water end-use-based structure, including a PRP-based stochastic model at the daily time scale (Blokker et al., 2010), and an agent-based model at an annual time scale (Chu et al., 2009).

The simulation time-step also affects model characteristics and capabilities. In general, small time-steps (from hourly to seasonal) are used for short- (less than a year) and medium-term (from one to ten years) models. These models are developed for system operations and assessment of pumping requirements, with focuses on demand changes under a fixed or slowly-changing customer base, and seasonal variations in demands, for example (Billings and Jones, 2008). Time-series, regression analysis, and artificial neural network model are common methods here; see examples provided by Donkor et al. (2014). In contrast, longer time-steps up to the annual scale are usually used for long-term (often a decade or more) planning and management to address questions related to infrastructure sizing (Billings and Jones, 2008), uncertainties associated with changing socio-economic conditions, and climate change. See, for example, Donkor et al. (2014), Qi and Chang (2011), Gober et al. (2011), and Qaiser et al. (2011).

Historically, water demand models have focused on economic factors as driving residential water demand (Arbués et al., 2003; March and Saurí, 2009; Grafton et al., 2011). Therefore, demand models often incorporate economic factors as water-use drivers, and include their effects on the viability of management options. For example, water price and family income are widely included in time-series and regression models through estimation of price and income elasticities (March and Saurí, 2009). However, a variety of studies have shown that residential water demand is rather inelastic (Arbués et al., 2003), and actually responds more to income, climate, institutional characteristics, and demographics than to price (Palazzo et al., 2017). Conservation efforts also play an important role, and utilities in Canada have faced a reduction in revenues (Di Matteo, 2016; CBC News, 2015) as household water use has decreased over the past several decades across North America (DeOreo et al., 2016), at the same time the utilities must upgrade their water systems. Interestingly, the apparent solution has been to increase the fixed component of the water bill, and reduce the component related to variable consumption charges; however, this reduces the economic incentive for households to conserve water (Di Matteo, 2016). Several recent studies have analyzed municipal management policies in terms of trade-offs between various water supply expansion options, system rehabilitation options, and water reuse infrastructure. For example, Chung et al. (2009) used an optimization model that incorporated system reliability to minimize the economic cost of municipal supply design. They found a lower cost for expanding an existing water treatment plant than for building a new canal or pipeline. Rehan et al. (2011) analyzed the effects of rehabilitation strategies on the financial sustainability of water and wastewater services through changing user fees. Barton and Argue (2009) investigated cost implications of water reuse in a residential water planning model, and found that reuse infrastructure increased construction costs, but that these expenses were largely offset by savings in fees and charges. On the demand side, Olmstead and Stavins (2009) compared price and non-price measures such as water restrictions on water conservation, and generally found price-based approaches to be more cost effective, and more straightforward for monitoring and enforcement.

Finally, climate change presents uncertainties for demand modeling in terms of magnitude, timing, and possibly even the direction of changes in climate variables (House-Peters and Chang, 2011). An additional complication is that estimates of changing water availability (runoff) with climate change do not equal changes in water supply, because of complexity of water supply systems, which include water storage, transmission systems, treatment systems, and operating rules (Paton et al., 2013). Relatively few studies have explicitly modeled climate change effects on municipal water demand, and those studies that have included such effects typically found them to produce less significant effects than changes in population or water conservation efforts (Haque et al., 2014). For example, Haque et al. (2014) projected water demands to differ by 4 ML/year between three climate scenarios, while water use restrictions led to maximum reductions of 38 ML/year in 2040. Fowler et al. (2003) conducted a comprehensive study of the reliability, resilience, and vulnerability of the Yorkshire, UK, water system to historical and projected water resources droughts. They found that climate change is likely to drive increasing vulnerability of Yorkshire water resources to severe drought events, but their study omitted changing demands over the simulated period (to 2080), as well as alternative operating scenarios for the water supply system. Yung et al. (2011) assessed the risk to the Ayr, Ontario, Canada, water supply system from population growth, extreme projections of climate change, and demand management and/or supply expansion to 2025. In contrast to the results above, they found system reliability to differ only slightly between the population growth and climate change scenarios, while resiliency was better for the population growth scenario, and vulnerability was worse. Demand management had negligible effect, while supply expansion significantly improved all risk-based measures. Finally, Paton et al. (2013) assessed relative sources of uncertainty on water security for the southern Adelaide, Australia, water supply system. They included differences in climate scenarios, GCMs, demand projections, and stochastic rainfall time series, and found changing demand to be the greatest source of uncertainty.

3. Study area and data availability

Calgary is the largest city in Alberta, and had a population of 1.2 million people (about 37% of the provincial population) in 2014 (City of Calgary, 2014). Further, the city has had the highest annual growth rate among all Canadian cities over the last five years, with a 3.8% growth rate from 2012 to 2013 (Statistics Canada, 2016), and is projected to reach a population of 2.4 million by 2041 (Government of Alberta, 2015).

The city is concerned about water-use sustainability (City of Calgary, 2011), since the supply is limited by both its water license and the water treatment plant capacity. In terms of the water license, future water availability for Calgary is limited by the closure of the South Saskatchewan River basin to new water allocations in 2006 (Province of Alberta, 2007), while municipal consumption has

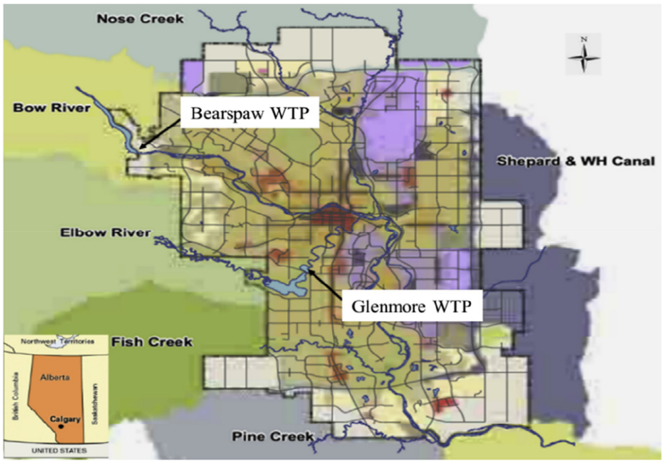

Fig. 1. City of Calgary location and water sources (City of Calgary, 2011).

averaged 72% of the peak-day production capacity over the past decade (Boulton-Chaykowski, 2016). At a regional scale, water is shared by diverse upstream and downstream users including farmers and irrigation districts, industrial users, and recreational activities (Ali and Klein, 2014; Percy, 2005), and their water demands are also increasing with population growth.

Adding to the challenges of population growth and limited allocations are potential impacts of climate change. Calgary depends heavily on consistent river flows primarily from the annual snowpack and glacial meltwater. The city has experienced increased temperatures, which can significantly increase outdoor demands, and decreased river flow over the last 100 years (Natural Resources Canada, 2007), and such trends are expected to continue (Rood et al., 2016). However, climate change impacts on temperature and precipitation are unclear. Recent studies project changes in seasonal precipitation of −15% to 25%, while seasonal temperatures may increase by up to 4.2 °C in Alberta by the 2050s (Jiang et al., 2015). For the Bow River Basin, changes of monthly mean precipitation could range from −1% to 8%, and monthly mean temperature is projected to increase by 2 °C–4.5 °C by the 2050s (Tanzeeba and Gan, 2012). The combined impact of these changes could decrease water availability (see section 2.2), as well as increase outdoor water demands during periods of hot, dry weather (House-Peters and Chang, 2011), and lengthen watering seasons.

3.1. *Water supply and demand*

Calgary is located in one of the driest regions in Canada with average annual precipitation and evapotranspiration of 413 mm and 405 mm respectively (Alberta Government, 2013). Calgary relies on two surface water sources, the Bow and Elbow rivers, which originate in the Rocky Mountains west of Calgary and flow eastward through the Canadian Prairies (Fig. 1). From these two water sources, the city has an annual licensed withdrawal of 460 million m^3 (AEP, 2015). Two water treatment plants, Bearspaw and Glenmore plants, located along the Bow and Elbow Rivers, respectively, are capable of providing up to 1 million m^3 of drinking water to the city each day (City of Calgary, 2015).

In 2013, the average residential water use in Calgary was 231 L per capita per day (lpcd; City of Calgary, 2013), which is 64% of the North American residential average of 360 lpcd (DeOreo et al., 2016). Calgary has reduced its per capita daily demand from an average total per capita demand of 500 lpcd in 2003 to 406 lpcd in 2010 (City of Calgary, 2011) through implementation of water conservation policies and low-flow technologies. Specific data are not available for Calgary, but Table 1 shows the average indoor fixture and appliance usage in 1999 and 2016 for North American cities (DeOreo et al., 2016). Despite these per capita decreases in water use, Calgary's total water demand continues to increase. Total water demand has almost doubled from 1972 (98 MCM, or million m^3; Headwater Communication, 2007) to 2015 (170 MCM; Boulton-Chaykowski, 2016) as the population has grown from approximately 400 000 in 1971 (Statistics Canada, 1977) to 1.4 million in 2015 (Statistics Canada, 2016).

Major water uses in Calgary (Fig. 2a) include residential; industrial, commercial, and institutional (ICI); non-revenue (street cleaning, firefighting, and losses); and wholesale supply to nearby communities. Residential indoor uses are typical for a North American city (DeOreo et al., 2016), as shown in Fig. 2b. Outdoor water use accounted for about 12% of total annual use in 2007 (Headwater Communications, 2007), a value much lower than the North American average of 50% (DeOreo et al., 2016), mainly because of the short growing season in Alberta. Calgary's outdoor use is known to increase significantly when weekly mean temperatures are higher than 10 °C (Chen et al., 2006) and is also affected by weekly rainfall (Akuoko-Asibey et al., 1993). In normal years, summer demand can be 170% of winter demand, and up to 250% of winter demand in hot and dry years (Natural Resources Canada, 2007).

3.2. *Water management and conservation*

Calgary uses the following evaluation criteria to assess its water management options: water conservation effectiveness, such as per capita demand reduction and peak daily demand reduction; cost-

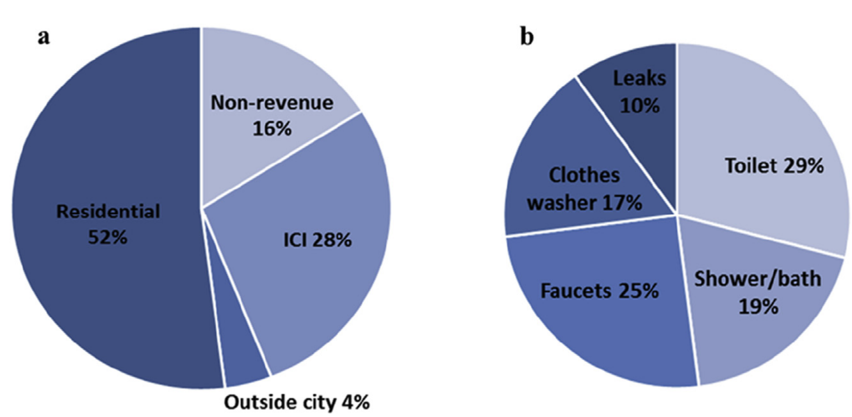

Fig. 2. Water use categories with percentages for the City of Calgary (a) and residential indoor uses (b) (City of Calgary, 2010).

effectiveness (\$ per m^3 of water conserved); and social impacts of water shortage, such as unmet water demand (City of Calgary, 2010). For the past decade, Calgary has adhered to a “30-in-30” plan (Headwater Communications, 2007), which targets the same volume of water withdrawal in 2033 as in 2003 by reducing per capita water demand by 30 percent (from 500 lpcd to 350 lpcd) over those 30 years. A 2015 assessment found that the city was on track to its goal (City of Calgary, 2016). Calgary has implemented water metering, encouraged adoption of water-efficient appliances such as low-flow toilets, offered economic incentives, improved leak detection efforts, and educated citizens about water use and conservation. For example, Calgary's water metering rate increased from 44.5% in 1996 to 97% in 2014, and the low-flow toilet incentive program awarded 75 000 rebates from 2003 to 2014 (Boulton-Chaykowski, 2016). The prevalence and water conservation effectiveness of a variety of water management policies are discussed in the Supplementary Material (see Table S1).

4. Calgary Water Management Model (CWMM)

The Calgary Water Management Model (CWMM) is a system dynamics model that simulates municipal water demand and use, and treatment plant water withdrawals, at a weekly timescale, beginning in 1996 and ending in 2040, to aid both near-term evaluation of water-use characteristics and long-term planning and management of regional water resources. Its novelty lies in its application of a system dynamics framework at a weekly time step to municipal water management, its ability to reveal the water requirements of specific end-uses and the relative effects of both technological and policy changes, and its ability to simulate conservation policy effects and their economic trade-offs. CWMM includes interactions between increases in municipal water demands with population growth, the available water supply, and the effects on demand of climate change and water conservation policies, including those described in Table S1: water metering, low-flow appliances, rain barrels, leak management, educational programs, economic incentives, water rationing, greywater reuse, and xeriscaping. The model is described briefly below; a detailed description is provided in the Supplementary Material.

4.1. Model structures and interface

In each simulation run, CWMM first simulates the water demands of various end-uses in liters per capita per day, and then sums them to generate total per capita water demands. The model subdivides municipal water demand into ten end-use categories, based on Mayer et al. (1999) and Coomes et al. (2010): toilet, shower and bath, laundry, kitchen, leaks, other, outdoor, ICI (industrial, commercial, and institutional), non-revenue (for street-cleaning and firefighting, for example), and extra-municipal (water wholesale) uses – see Fig. 3. The per capita daily water demand

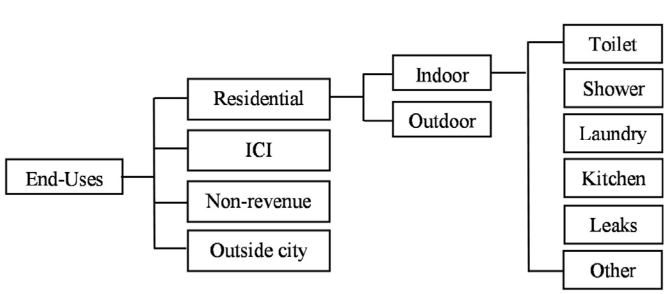

Fig. 3. Municipal water end-uses (adapted from Coomes et al., 2010).

of each residential indoor end-use is calculated according to a combination of the base per-use demand, number of daily uses, and fraction of households equipped with water conserving fixtures and appliances (Table 1). Per capita outdoor demands are based on weekly temperature and rainfall, and modify a set of climate-based relationships developed for Calgary by Chen et al. (2006) and Akuoko-Asibey et al. (1993); see the Simulation of the Per Capita Municipal Water Demand section in the Supplementary Material for further details.

To calculate the total municipal demand, the model multiplies the per capita demands with the municipal population and adds ICI, non-revenue, and wholesale demands. This total demand is compared with the available water supply to determine the weekly water withdrawal. Finally, the withdrawn water is used to satisfy water demands, and if demands cannot be fully satisfied, a water shortage is generated and represented as an “unmet water demand”, as explained in Wang and Davies (2015). This unmet demand can drive more rapid adoption of low-flow fixtures and appliances, and the implementation of conservation policies such as rationing. The effects of water conservation policies are simulated either by increasing the adoption rates of low-flow fixtures and appliances or by decreasing specific end-use demands directly. Policy application costs are modeled using a conservation cost per unit (\$/m^3) multiplied by the amount of water conserved, the adoption cost of each low-flow appliance or xeriscaping of each property multiplied by the change in percentage of low-flow appliance adoptions or the percentage of properties converted from turf to xeriscaping.

The model has a user-friendly interface (Fig. 4) that facilitates the construction of various population and climate change scenarios, as well as policy selection among the available management policies. Sliders are used to select among policies – for example, “0” means off and “1” means on – or to set policy application intensities to specific values. The model interface also displays results such as weekly and per capita water demands for specific water end-uses, or can display results from multiple scenarios simultaneously to permit comparison among different options. Finally, CWMM supports both a “scenario mode”, where pre-set values are used for a single, continuous simulation run from 1996 through 2040, and a “gaming mode”, which allows users to refine policy selections at a week-by-week (to longer) time step over the 1996–2040 time period.

4.2. Model validation

The following tests were used to validate the model (Barlas, 1994; Sterman, 2000): 1) model structure and parameter tests confirmed that mathematical equations and interrelationships adequately represent the corresponding system in the real-world; 2) extreme conditions tests ensured that the model generated reasonable results even with extreme values assigned to model parameters; 3) sensitivity analyses permitted investigation of the model responsiveness to important uncertainties in model equations and parameters; and 4) key model outputs such as per capita water demand, weekly water demand, and total water withdrawal were compared with historical values to ensure that the model could replicate historical behavior. Fig. 5a compares observed and simulated water demands for the historical period of 2005–2015.

The first three tests and key model assumptions are discussed in the Model Validation and Model Assumptions sections of the Supplementary Material. Further, several statistical performance measures were used to quantify differences between the simulated and observed municipal water use at a weekly scale. The coefficient of determination (R^2) and root mean square error (RMSE) were used to evaluate, respectively, the magnitude of variance explained

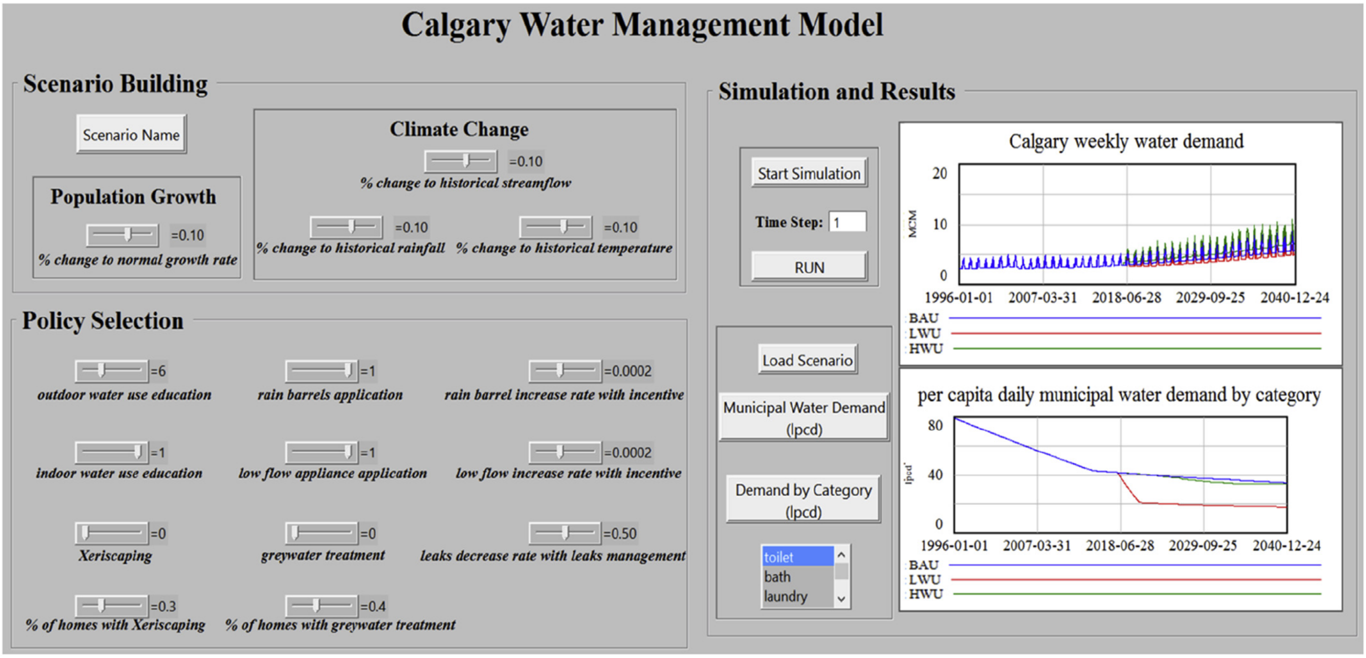

Fig. 4. The model's user-friendly interface. The scenarios shown on the right side of the figure are Business as Usual (BAU), Low Water Use (LWU), and High Water Use (HWU).

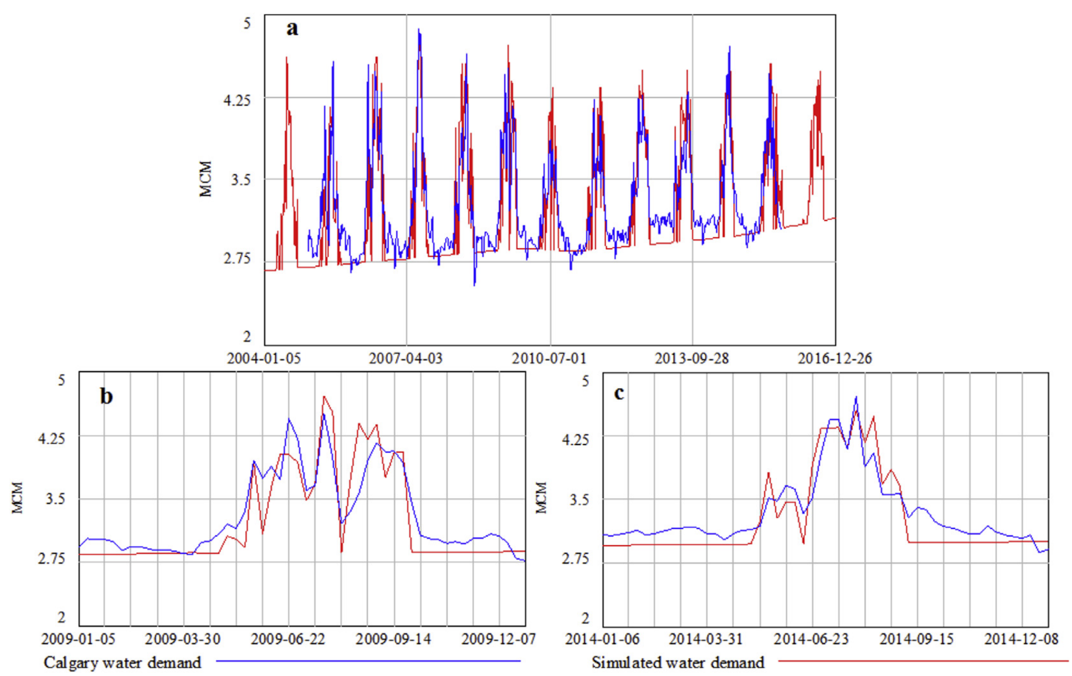

Fig. 5. Comparison of observed and simulated municipal water demands for 2005–2015 (a), 2009 (b), and 2014 (c).

by the model compared with the total observed variance, and the average differences between simulated and observed demands (in MCM; million m^3). The normalized root mean square error (NRMSE) represents the normalized RMSE (in %), and the mean bias error (MBE) indicates over/underestimation (in MCM) by CWMM. In particular, use of RMSE and MBE, both measured in MCM, would permit utilities to estimate potential effects on costs and revenues associated with model error.

Performance measure results for the 2005–2015 period used an average actual weekly demand of 3.3 MCM, and produced values as follows: $R^2 = 0.80$, RMSE = 0.19 MCM, NRMSE = 5.76%, and MBE = −0.08 MCM. Although these values are relatively poorer than those achievable by other methods described in section 2, it is important to recall that these values represent a full decade of simulated water consumption figures at a weekly scale with relatively small error. We also calculated performance measures for several representative years to provide more detailed comparisons between simulated and observed data at a weekly time scale – see Fig. 5b and c for the details of 2009 (Fig. 5b) and 2014 (Fig. 5c), and Table 2 for six years of the historical period. For 2007, 2012, and

Table 2
Sample statistical performance measures for CWMM for the 2005–2015 period.

Year	R^2 (–)	RMSE (MCM)	NRMSE (%)	MBE (MCM)	Mean (MCM)
2005	0.62	0.24	7.73%	−0.17	3.15
2007	0.87	0.20	6.18%	−0.09	3.22
2009	0.81	0.21	6.32%	−0.08	3.31
2012	0.87	0.14	4.19%	−0.10	3.31
2014	0.87	0.15	4.46%	−0.14	3.35
2015	0.70	0.23	6.75%	−0.08	3.40

2014, the simulated demands were quite close to the observed values; in contrast, model performance in 2005, 2009, and 2015 was relatively poorer.

The simulated and observed patterns differed in several important ways: 1) during winter seasons, the simulated water use fluctuated less – it is affected only by population growth and low-flow fixture or appliance adoption in CWMM – than the observed values, since neither seasonal behavioral changes nor specific events such as water-main breaks, street cleaning and sewer line flushing, fire event responses, social events (conferences, expositions, or sporting events), holiday periods, or car washing (Boulton-Chaykowski, 2016) were modeled; and 2) during summer seasons, simulated weekly water use varied both upwards and downwards from observed values, because of the model time-step and simplifications, and the unpredictability of outdoor water use behavior. Despite these differences, in most simulated years, the winter demand as simulated in CWMM is representative of the observed, relatively flat pattern (see Fig. 5b and c), with notable deviations in 2012–13 and 2013–14. In terms of summer values, the effects of sub-weekly weather variations on outdoor water use accounted for many of the differences between simulated and observed values. For example, in the week of June 1, 2009, the simulated demand value (3.1 MCM) was lower than the observed value (3.7 MCM), because weekly mean temperature and rainfall values of 8.9 °C and 8.6 mm substantially reduced simulated outdoor use (Fig. 5b). However, daily weather data show two cold, rainy days (June 5 and 6) during this period, with mean temperatures of 5.9 °C and 4.2 °C and rainfall of 5.4 mm and 3.2 mm, while the preceding several weeks were hot and dry, which suggests that outdoor demands were still high during that week, prior to June 5 and 6.

5. Results and discussion

5.1. Model forecasting and water demand scenarios

Four scenario groups, with a total of seventeen scenarios, were developed for an investigation of Calgary's potential future water demands under various degrees of population growth, climate change, and water conservation policy implementations – see Table 3 for the scenario details. Water use, which can be lower than water demand under water stress conditions, is discussed in some scenarios, where appropriate. Conservation policies are applied from 2018 onwards, and scenario comparisons are shown for the period of 2015–2040.

Scenario group 1 focuses on climate change and population growth effects – these are the most commonly assessed variables in water demand studies and provide comparison points for other scenarios. First, climate change scenarios that included increased temperature, decreased streamflow, and increased precipitation were simulated, while population growth rates were held fixed. Several recent studies have projected 10%–20% increases in temperature and precipitation and decreases in streamflow due to higher evapotranspiration (Jiang et al., 2015; Rood et al., 2016; Tanzeeba and Gan, 2012) during spring and summer seasons in Alberta, while another recent study revealed a rate of global warming from 2000 to 2015 as fast as, or even exceeding, that of the last half of the 20th century (NOAA, 2016). Therefore, the scenarios here included 10%, 20%, and 30% changes in climate variables under normal population growth conditions. Second, three different population growth rates relative to the normal growth rate were tested under constant climate conditions. The normal population growth rate was adapted from historical and projected population

Table 3
CWMM set-up for the four scenario groups.

Simulation groups and scenarios[a]		Detail set up									
		Population and climate set up			Policy selection[b]						
		Change in pop growth rate	Temp. change rate	Streamflow and rainfall change rate	Edu	EI	LM	GR	% of GR	% of Xer	WR
1	NG_CC_10%	0	10%	−10%, 10%	X	X	X				
	NG_CC_20%		20%	−20%, 20%	X	X	X				
	NG_CC_30%		30%	−30%, 30%	X	X	X				
	PG_-10%_NC	−10%	0	0, 0	X	X	X				
	PG_10%_NC	10%			X	X	X				
	PG_20%_NC	20%			X	X	X				
2		10%	10%	−10%, 10%							
	BAU[c]	0	0	0, 0	X	X	X	N	5	30	
	LWD	0	0	0, 0	X	X	X	N	50	80	
3	HG_CC_EI	10%	10%	−10%, 10%		X					
	HG_CC_GR							N	100		
	HG_CC_Xer									100	
	HG_CC_WR										X
4	HG_CC_GR_20%	10%	10%	−10%, 10%				N	20		
	HG_CC_GR_50%							N	50		
	HG_CC_GR_80%							N	80		
	HG_CC_GR_100%							F	100		

[a] Scenario name abbreviations: NG = normal population growth, HG = high population growth, PG = population growth, CC = climate change, NC = non-climate change, HWD = high water demand, BAU = business as usual, LWD = low water demand.
[b] Policy abbreviations: Edu = education, EI = economic incentive, LM = leak management, GR = greywater reuse, Xer = xeriscaping, WR = water rationing, N = normal reuse (toilet, outdoor, and ICI), F = full reuse (all end-uses except kitchen), X = policy is turned on.
[c] A greywater reuse percentage of 5% is debatable; however, recent news and industry reports (CBC News, 2013; Lowes, 2017) indicate that greywater systems are increasingly common in new houses in Calgary. "Xeriscaping" in the business-as-usual case is intended to represent land use change as well as behavioral changes (primarily turf watering) believed to have reduced residential water use in the past decade or so.

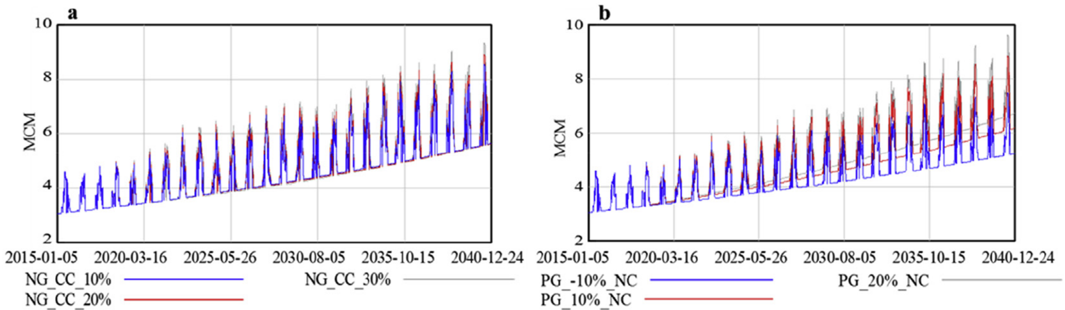

Fig. 6. Calgary weekly water demand under climate change (a) and population growth (b) scenarios.

values provided by the Government of Alberta (2015) with an average of 2.6% each year, while the low-growth scenario applied a 10% reduction in the growth rate (a value that actually occurred in 2010), and the higher-growth scenarios applied 10% and 20% increases to the normal growth rate. Under these three scenarios, the population of Calgary reaches 2.1, 2.5, and 2.7 million people by 2040, respectively.

In scenario group 2, three scenarios with different population growth rates, climate change conditions, and water management policy adoptions were tested against Calgary's "30-in-30" water management goals; they were called the high water-demand (HWD), business-as-usual (BAU), and low water-demand (LWD) scenarios – see Table 3. These scenarios were intended to represent a realistic range of future water demand conditions, where HWD had a high population growth rate, moderate climate change, and minimal effort to conserve water (using only low-flow appliances and rain barrels), BAU had a normal population growth rate without climate change and continued historical management policies and land use trends, such as economic incentives and a fixed percentage of households with xeriscaping, and LWD also used normal population growth rates, without climate change, and implemented xeriscaping, and greywater reuse policies more broadly.

Scenario group 3 focused on policy trade-offs, with four policies – economic incentives, greywater reuse, xeriscaping, and water rationing – adopted separately in 2018. Their water use, social impacts (represented by unmet water demands), and application costs were simulated under high population growth and climate change conditions. Note that the costs of economic incentives programs were based on the City of Calgary's toilet rebate program (Headwater Communications, 2007), the municipal share of greywater system and water rationing costs were Australian values taken from Alberta WaterSMART (2011) and Turner et al. (2007), and xeriscaping costs were estimated from a xeriscaping program in Southern Nevada, USA (Sovocool, 2005). Although all costs were adjusted to the same base year (2016 Canadian dollars), the simulated policy costs may not be representative of the situation in Calgary.

Scenario group 4 focused on greywater reuse in terms of conservation impact and policy cost, where the individual scenarios applied various greywater reuse intensities under high population growth and climate change conditions. Four greywater reuse scenarios represented percentages (20%, 50%, 80%, and 100%) of homes and ICI users with greywater reuse. Further, based on assumptions in Alberta WaterSMART (2011), the first three scenarios also imposed water demand reductions of 50% for toilets, 20% for outdoor use, and 10% for ICI purposes, while the fourth scenario (100% greywater reuse) reduced all end-use demands by 50% except kitchen water uses. Note that the greywater reuse policy is phased-in over three years for all scenarios of this group.

5.2. Model forecasting and scenario results

Model outputs for the six scenarios of group 1 are shown in Fig. 6. The applied climate change conditions clearly increased maximum weekly water demands during summer seasons (Fig. 6a) by increasing outdoor water demand; they also produced longer outdoor watering seasons. Specifically, the changes in climate increased maximum seasonal demands in all three scenarios, with a range from a minimum of 4.9 million m^3 in summer 2018 to a maximum of 9.3 million m^3 in summer 2040 for the NG_CC_10% and NG_CC_30% scenarios, respectively. Further, maximum demand for NG_CC_30% was 1% and 9% higher than the NG_CC_10% in 2018 and 2040, respectively. Interestingly, during lower water-demand seasons, NG_CC_30% had relatively lower demand than the other scenarios because of a model feedback that altered model behavior in response to repeated water shortages: higher unmet summer demands drove relatively greater adoption of water conserving fixtures and appliances, such as low-flow toilets and washing machines, which then resulted in greater conservation indoors during the winter. After 2038, all three scenarios were close to their maximum low-flow fixture adoption levels and therefore had similar winter demands (Fig. 6a). Finally, at an annual scale, outdoor water demand represented only about 10% of the total, and water use patterns were assumed not to change under climate change; therefore, climate change did not change Calgary's annual water demand significantly. However, CWMM does not simulate changes in water supply, and at a weekly scale, the potential for significant increases in maximum water demands during warmer summers of the future may require further study.

Compared to the climate change scenarios, weekly water demand was significantly more sensitive to population growth (Fig. 6b). Specifically, the population growth scenarios significantly increased water demand in all seasons over the simulation period. For example, the maximum demand of PG_20%_NC was greater than PG_-10%_NC by less than 1% in 2018, and by more than 20% in 2040.

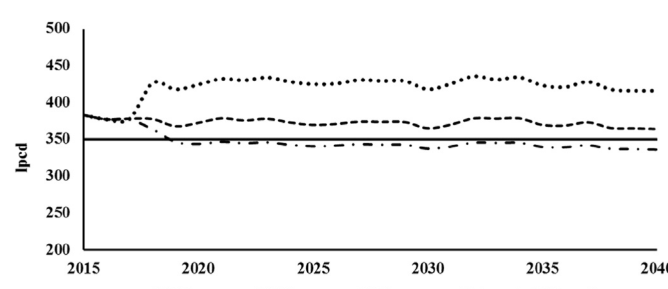

Fig. 7. Annual average per capita daily water demand. The scenarios shown are Business as Usual (BAU), Low Water Use (LWU), and High Water Use (HWU).

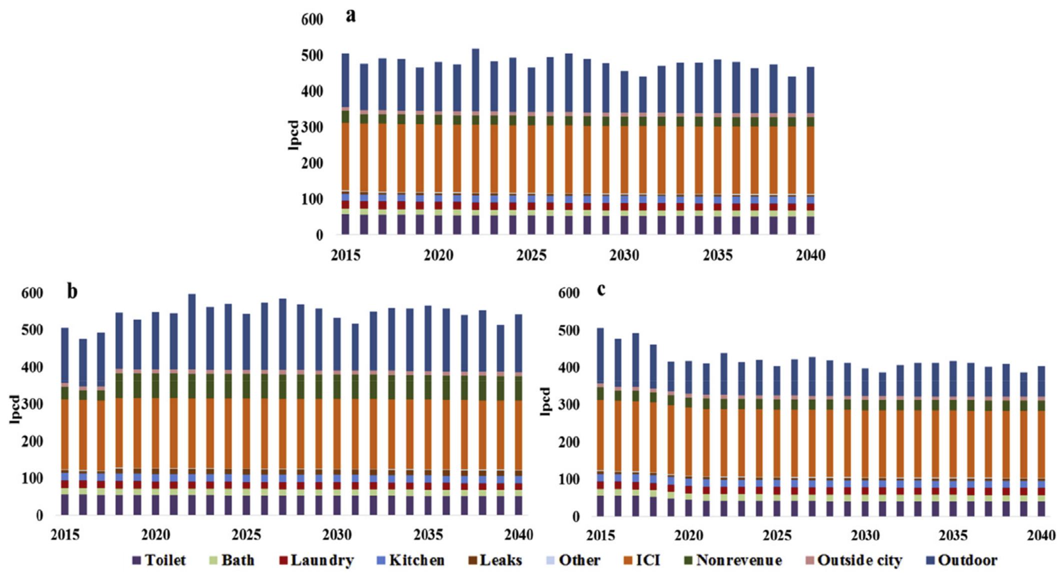

Fig. 8. Components of peak per capita daily water demand of the BAU (a), HWD (b), and LWD (c) scenarios.

For the three scenarios of group 2, the model produced significantly different values for annually-averaged per capita daily water demands (Fig. 7). From 2015 onward, the decreasing trends of all three scenarios slowed – as compared with the historical period – since water-metering was already 97% in 2014 and low-flow shower head and toilet adoption percentages approached their theoretical maxima (85%, according to Rogers, 1995). Therefore, HWD and BAU had annually-averaged per capita daily demand values of 426 lpcd and 372 lpcd, respectively, from 2020 to 2040. To continue to decrease water demands, a broader implementation of greywater reuse and xeriscaping policies simulated by LWD reduced the per capita daily demand to 340 lpcd in 2020, below the management goal of 350 lpcd.

In addition to total municipal demand, the model also simulated the water demands of each end-use. Comparing these end-uses across scenarios clarifies the impacts of population growth, climate change, and management policies on the total demands shown in Fig. 7 – see Fig. 8, which shows the components of the annual peak-daily per capita demand for the three scenarios. Compared to BAU, HWD had higher leakage losses (50% higher) and outdoor water demand (about 16% higher) because of reduced leak management efforts and gradually increasing temperatures after 2018 with climate change. In the LWD scenario, toilet, outdoor, and ICI water demands decreased from BAU levels by 20%, 35%, and 4%, respectively, as a result of broader implementation of greywater and xeriscaping policies after 2018.

Scenario group 3 illustrates weekly water use and unmet demand values for four different conservation options under high population growth and climate change conditions from 2018 to 2040 – see Fig. 9. To compare these policies, adoption of each conservation option was simulated individually. CWMM simulated similar water-use levels for the economic incentives and xeriscaping scenarios, but xeriscaping reduced summer-season weekly water use by a maximum of 10% (a difference of 540 000 m^3 in the peak-demand week) and increased non-summer season water use by 0.5%, compared with economic incentives. The reason for the difference was that xeriscaping only reduced outdoor use during the summer season while economic incentives affected indoor, outdoor, and ICI uses in all seasons by increasing the adoption rate of low-flow fixtures and appliances, which reduced non-summer uses relative to the xeriscaping scenario (see Fig. 9a). Under water stress conditions after 2022, both scenarios used the maximum water supply during the summer. Water rationing, the third scenario of group 3, had very similar water use (0.2% higher) to economic incentives in all seasons; however, compared to xeriscaping, its summer use was 10% higher – because water rationing used all the available water during the high-demand summer season – while use in other seasons was 1% lower, as a result of a 2% greater low-flow fixture and appliance adoption rate (Fig. 9a). This high adoption rate resulted from the high level of unmet demand during

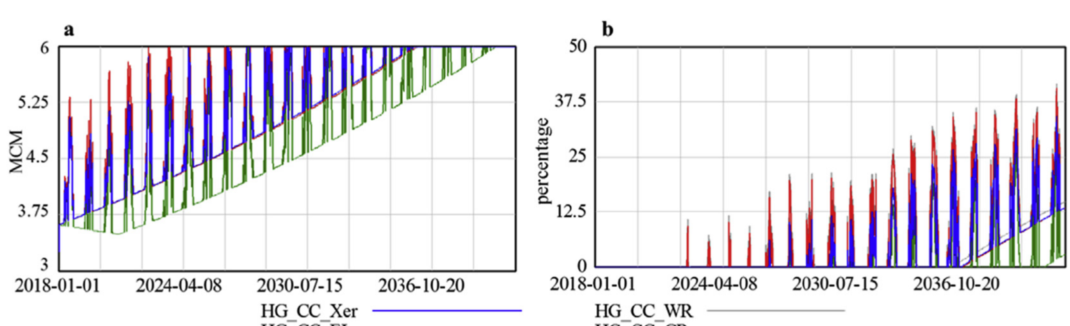

Fig. 9. Weekly municipal water use (a) and unmet water demand (b).

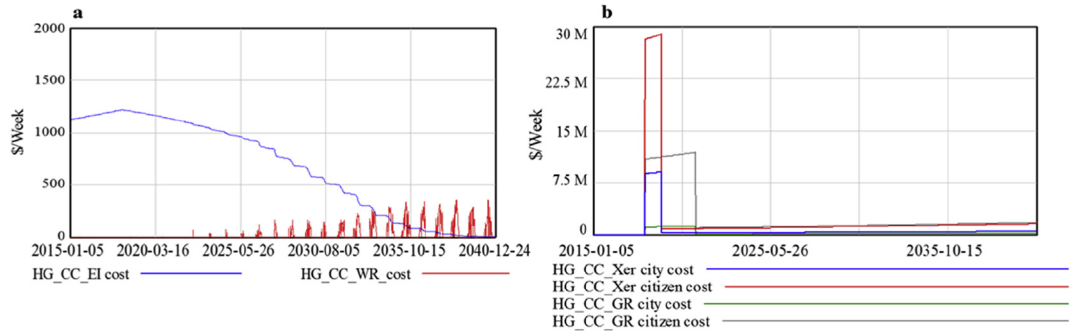

Fig. 10. Weekly costs for economic incentive and rationing (a) and xeriscaping and greywater reuse (b) policies.

summer (Fig. 9b), which drove a greater low-flow appliance adoption rate through model feedbacks. Finally, greywater reuse, the fourth policy of the group, was the most effective policy in reducing weekly water use in all seasons: it produced a 14% reduction in water use and a low unmet demand under both stress and no-stress conditions (Fig. 9b).

Group 3 scenario costs were also simulated, based on details provided in the Simulation of Water Policies section of the Supplementary Material. Their order, ranked from lowest to highest cost, was rationing, economic incentives, xeriscaping, and greywater reuse. Fig. 10a compares economic incentives with water rationing costs, and shows economic incentive costs decreasing from about $1200 to nearly $0 per week from 2018 to 2040. This decreasing trend resulted from the saturation of households with low-flow fixtures and appliances. For example, low-flow toilets were installed in close to 70% and 80% of homes in 2018 and 2040, respectively; therefore, there was little uptake of the economic subsidy later in the simulation period. In contrast, water rationing had a relatively low cost when applied during water shortages (Fig. 10a), but caused high unmet water demand (Fig. 9b). Xeriscaping had the highest cost of all four scenarios in the first application year (Fig. 10b) – approximately $1450 million per year for a 100% application rate – for the conversion of all lawns in the city to xeriscaping; however, costs were relatively lower in the following years (approximately $60 million per year) to provide 100% of new homes with xeriscaping (Fig. 10b). Finally, greywater reuse had the highest total cost, at $570 million per year over three years for a 100% application rate of the normal reuse scenario, as well as the longest implementation time (Fig. 10b). Note that all implementation costs are approximate, and that implementation times for the xeriscaping and greywater reuse policies are modeled with delays that can be changed to simulate different conditions in other cities. CWMM can also calculate the unit water saving cost ($/m^3 saved; not shown here) for further comparison of policies.

Finally, scenario group 4 tested several application intensities of the greywater reuse policy under high population growth and climate change conditions. Differences among the weekly water demands of the HG_CC_GR_20%, 50%, and 80% scenarios were not large, with a maximum 8% difference (Fig. 11a) between them. The reasons are that their major effect is on toilet water demand (reduced by 50%), which represents 14% of the total municipal water demand, and outdoor and ICI uses, which represent about 10% and 28% of the total municipal demand, and are reduced by 20% and 10%, respectively. In contrast, full application of the greywater reuse policy (HG_CC_GR_100%) dramatically reduced total weekly water demand – by 44%, compared with the HG_CC_GR_20% scenario, for example (Fig. 11a). In reality, of course, the efficacy of the greywater reuse policy would depend heavily on the quality of treated water and its suitability for different water end-uses, as well as the implementation cost (Fig. 11b). Here, the municipal share of the application cost for the 100% policy was approximately three times higher (at $120 million per year, or $80 million per year above the next highest scenario) than in the other three scenarios.

5.3. Discussion

Application of CWMM to Calgary revealed that adoption of several water conservation policies will ensure water availability under future population growth, a limited water license, and uncertainties from climate change. The model showed that weekly water demand was more sensitive to population growth than to climate change. Further, City of Calgary is on its way to achieving its "30-in-30" goal, and may achieve further demand reductions through a wider application of xeriscaping and greywater treatment and reuse programs. At an annual scale, these policies could reduce water demand per person per day by 10% relative to the BAU

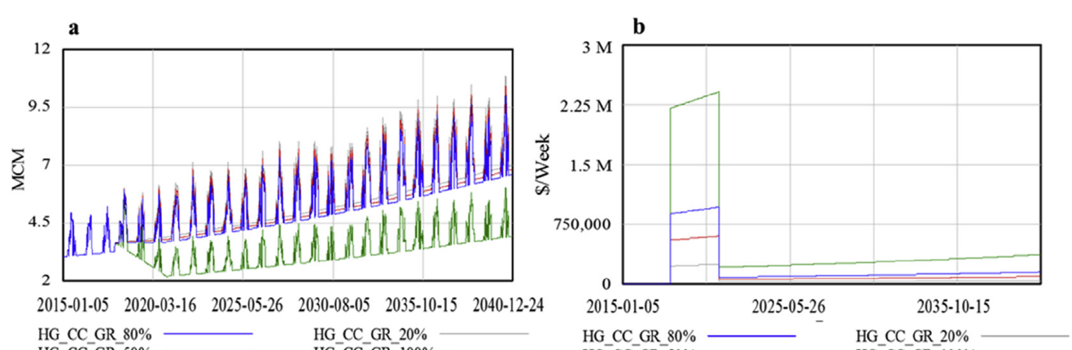

Fig. 11. Weekly municipal water demand (a) and municipal share of the cost (b) of greywater reuse.

scenario. In particular, xeriscaping reduced the maximum municipal water use during the summer season by an average of 10%, while adoption of low-flow appliances and greywater reuse affected end-uses in all seasons. Water rationing resulted in high unmet water demands (here, a maximum of 40% of the total demand); however, it is a relatively inexpensive conservation approach. Indeed, implementation costs represent the main tradeoff of conservation policies for both the city and its citizens. For example, greywater reuse in CWMM reduced water use by 14% during hot and dry conditions, as compared with water rationing, but required approximately $60 million per year for three years from the city government in one scenario (100% application with normal reuse) to implement the required infrastructure. Note that such economic figures are uncertain and require further research.

6. Conclusions

This paper introduced a system dynamics model for Calgary, Alberta, as an alternative to commonly-used time-series analysis, regression analysis, stochastic modeling, and artificial intelligence (AI) approaches. The Calgary Water Management Model (CWMM) supports water resources management and planning under various population growth and climate change conditions, and the implementation of alternative water conservation policies. Intended for use as a seasonal-to decadal-scale decision-support tool, CWMM adopts, (1) a process-based, end-use oriented structure with ten individual water end-uses, (2) a weekly calculation time-step, and (3) a user-friendly data-entry system and graphical user interface. The end-use based structure permits simulation of the impacts of nine water management policies, including conservation education, leak management, economic incentives, water rationing, low-flow appliances, rain barrels, water metering, xeriscaping, and greywater reuse, on specific municipal end-uses. Further, the weekly time-step reveals seasonal water demand patterns and their responses to various management policies, and facilitates investigation of system capacity in high water-demand seasons as well as alternative climate change scenarios.

Several model limitations will be addressed through future research. Although adoption of low-flow fixtures and appliances is, at least partially, an economic decision, the current version of CWMM does not incorporate water price. The addition of water pricing would permit simulation of potential changes in demand with changes in price, the relative cost-effectiveness of alternative system expansion or conservation options, comparative policy payback times for options such as xeriscaping and greywater reuse, and could improve the simulation of low-flow fixture adoption rates in response to price signals. However, all of these changes would require data collection. For example, the first model improvement would require data that correlate economic drivers to specific water end-uses, the second and third would require detailed, location-specific economic data and projected trends, and the last would require customer interviews and surveys, as well as the inclusion of other possibly important signals beyond price (Palazzo et al., 2017). The inclusion of water price and water supply infrastructure (e.g. Rehan et al., 2011) could also permit an examination of the positive feedback between decreasing water consumption, falling utility revenue and rising rehabilitation costs, and increasing price, and possibly show effects of the shift toward a larger fixed cost component in water bills. Other model improvements could incorporate variable winter demands, if correlations could be established between climate variables and water-main breaks in cold weather, car washing during warm periods, residential outdoor use for hockey rinks and spas, and institutional, commercial, and industrial (ICI) uses, for example. Disaggregation of residential uses to detached- and multi-unit housing, and to regions of the city, would permit (1) a more detailed analysis of infrastructure needs, and (2) more sophisticated model validation approaches. Such an approach would also allow a more detailed representation of turf and landscape irrigation, and potential effects of changing land use over time. Disaggregation of industrial, commercial and institutional (ICI) water end-use would allow investigation of alternative industrial and commercial development pathways, as well as sector-specific policies. Finally, daily or even hourly time-steps could be simulated, if data at these levels were available.

The City of Calgary was the focus of the model development, but the resulting CWMM framework is suitable for other cities facing similar water resources management and planning challenges. CWMM is intended to provide comprehensive decision-support for municipal water managers, planners, researchers, and modelers. A modified model may also assist with city water resources management and assessment, drought preparedness and mitigation, long-term water resources planning, and public engagement and education.

Acknowledgements

The authors thank A. Boulton-Chaykowski and others at the City of Calgary for their interest and help, and for the data they provided. This research was supported by a grant from the Alberta Land Institute at the University of Alberta, Canada.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.envsoft.2017.12.024.

References

Ahmad, S., Prashar, D., 2010. Evaluating municipal water conservation policies using a dynamic simulation model. Water Resources Management 24, 3371–3395.
Akuoko-Asibey, A., Nkemdirim, L.C., Draper, D.L., 1993. The impacts of climatic variables on seasonal water consumption in Calgary, Alberta. Can. Water Resour. J. 18, 107–116.
Alberta Environment and Parks (AEP), 2015. Water allocation license viewer. http://maps.srd.alberta.ca/LicenceViewer/ (accessed November 2016).
Alberta Government, 2013. Evaporation and Evapotranspiration in Alberta. Edmonton, Alberta, Canada. https://agriculture.alberta.ca/acis/docs/mortons/mortons-evaporation-estimates.pdf (accessed December 2016).
Alberta WaterSMART, 2011. Greywater Recycling and Reuse in Alberta. Alberta Finance and Enterprise, Edmonton, AB, p. 22. http://www.albertawatersmart.com/reports/publicly-released-reports/water-reuse/8-greywater-recycling-and-reuse-in-alberta-2011/file.html (accessed September 2016).
Alessi, S., Kopainsky, B., 2015. System dynamics and simulation/gaming: overview. Simulat. Gaming 46, 223–229.
Ali, M.K., Klein, K.K., 2014. Implications of current and alternative water allocation policies in the bow River sub basin of southern Alberta. Agric. Water Manag. 133, 1–11.
Arbués, F., García-Valiñas, M.Á., Martìnez-Espiñeira, R., 2003. Estimation of residential water demand: a state-of-the-art review. J. Soc. Econ. 32, 81–102.
Barlas, Y., 1994. Model Validation in System Dynamics. International System Dynamics Conference. Stirling, Scotland).
Barton, A.B., Argue, J.R., 2009. Integrated urban water management for residential areas: a reuse model. Water Sci. Technol. 60, 813–823.
Billings, R.B., Jones, C.V., 2008. Forecasting urban water demand. Chapter 1 Introduction to Water Forecasting, second ed. American Water Works Association, Denver, Colorado.
Blokker, E.J.M., Vreeburg, J.H.G., Van Dijk, J.C., 2010. Simulating residential water demand with a stochastic end-use model. J. Water Resour. Plann. Manag. 136, 19–26.
Boulton-Chaykowski, A., 2016. Calgary Total Water Supply and Demand. Personal Communication, City of Calgary Water Management Analyst. Water Centre, 625 25th Avenue, Calgary, AB, Canada.
Brown, C.M., Lund, J.R., Cai, X., Reed, P.M., Zagona, E.A., Ostfeld, A., Hall, J., Characklis, G.W., Yu, W., Brekke, L., 2015. The future of water resources systems analysis: toward a scientific framework for sustainable water management. Water Resour. Res. 51, 6110–6124. https://doi.org/10.1002/2015WR017114.
Brown, K., 2002. Water Scarcity: forecasting the future with spotty data. Science 297, 926–927.

Canadian Broadcasting Corporation (CBC News), 2013. Homemade grey water recycling system shut down by city. http://www.cbc.ca/news/canada/calgary/homemade-grey-water-recycling-system-shut-down-by-city-1.1325770 (accessed April 2017).
Canadian Broadcasting Corporation (CBC News), 2015. Water rates need overhaul, says Ottawa city staff. http://www.cbc.ca/news/canada/ottawa/water-rate-charges-need-overhaul-says-ottawa-city-staff-1.3072131 (accessed October 2017).
Chen, Z., Grasby, S.E., Osadetz, K.G., Fesko, P., 2006. Historical climate and stream flow trends and future water demand analysis in the Calgary region, Canada. Water Sci. Technol. 53, 1–11.
Chen, Z., Wei, S., 2014. Application of system dynamics to water security research. Water Resources Management 28, 287–300.
Chu, J., Wang, C., Chen, J., Wang, H., 2009. Agent-based residential water use behavior simulation and policy implications: a case-study in Beijing City. Water Resources Management 23, 3267–3295.
Chung, G., Lansey, K., Bayraksan, G., 2009. Reliable water supply system design under uncertainty. Environ. Model. Software 24, 449–462.
City of Calgary, 2010. 2010 Water Efficiency Plan Update, p. 16. Calgary, AB. http://www.calgary.ca/UEP/Water/Documents/Water-Documents/Water_Efficiency_Update_2010.pdf (accessed December 2016).
City of Calgary, 2011. 2010 State of the Environment Report, p. 54. Calgary, AB. http://www.calgary.ca/UEP/ESM/Documents/ESM-Documents/2010-state-of-the-environment-report.PDF (accessed June 2016).
City of Calgary, 2013. Calgary 2013 Water Report, p. 8. Calgary, AB. http://www.calgary.ca/UEP/Water/Documents/Water-Documents/Water-Report.pdf (accessed June 2016).
City of Calgary, 2014. 2014 Civic Census Results, p. 133. Calgary, AB. http://www.calgary.ca/CA/city-clerks/Documents/Election-and-information-services/Census2014/Final%202014%20Census%20Results%20book.pdf (accessed August 2016).
City of Calgary, 2015. Calgary 2014 Water Report, p. 10. Calgary, AB. http://www.calgary.ca/UEP/Water/Documents/Water-Documents/Water-Report.pdf (accessed June 2016).
City of Calgary, 2016. Water Efficiency. http://www.calgary.ca/UEP/Water/Pages/Water-conservation/Water-efficiency.aspx (accessed December 2016).
Coomes, P., Rockaway, T., Rivard, J., Kornstein, B., 2010. North American Residential Water Usage Trends since, vol. 1992. Water Research Foundation, Denver, CO, p. 148. http://www.waterrf.org/PublicReportLibrary/4031.pdf (accessed November 2016).
Creaco, E., Blokker, M., Buchberger, S., 2017. Models for generating household water demand pulses: literature review and comparison. J. Water Resour. Plann. Manag. 143, 04017013.
DeOreo, W.B., Mayer, P., Dziegielewski, B., Kiefer, J., 2016. Residential End Uses of Water, Version 2. Water Research Foundation, USA, p. 243.
Di Matteo, L., 2016. Municipal Finances in Ontario – Growing Water Charges, Too. The Fraser Institute Blog. https://www.fraserinstitute.org/blogs/municipal-finances-in-ontario-growing-water-charges-too (accessed October 2017).
Dibike, Y., Prowse, T., Bonsal, B., O'Neil, H., 2016. Implications of future climate on water availability in the Western Canadian river basins. Int. J. Climatol. https://doi.org/10.1002/joc.4912.
Donkor, E.A., Mazzuchi, T.A., Soyer, R., Roberson, J.A., 2014. Urban water demand forecasting: review of methods and models. Journal of Water Resources Planning and Management-ASCE 140, 146–159.
Elsawah, S., Pierce, S.A., Hamilton, S.H., van Delden, H., Haase, D., Elmahdi, A., Jakeman, A.J., 2017. An overview of the system dynamics process for integrated modelling of socio-ecological systems: lessons on good modelling practice from five case studies. Environ. Model. Software 93, 127–145.
Eshtawi, T., Evers, M., Tischbein, B., Diekkruger, B., 2016. Integrated hydrologic modeling as a key for sustainable urban water resources planning. Water Res. 101, 411–428.
Ferraro, P.J., Price, M.K., 2011. Using Non-pecuniary Strategies to Influence Behavior Evidence from a Large Scale Field Experiment. National Bureau of Economic Research, Cambridge, MA.
Fowler, H.J., Kilsby, C.G., O'Connell, P.E., 2003. Modeling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system. Water Resour. Res. 39 (8), 1222,. https://doi.org/10.1029/2002WR001778.
Ghalehkhondabi, I., Ardjmand, E., Young, W.A., Weckman, G.R., 2017. Water demand forecasting: review of soft computing methods. Environ. Monit. Assess. 189, 313.
Ghiassi, M., Zimbra, D.K., Saidane, H., 2008. Urban water demand forecasting with a dynamic Artificial Neural Network model. J. Water Resour. Plann. Manag. 134, 138–146.
Gleick, P.H., 2003. Global freshwater resources: soft-path solutions for the 21st century. Science 302, 1524–1528.
Gober, P., Wentz, E.A., Lant, T., Tschudi, M.K., Kirkwood, C.W., 2011. WaterSim-a simulation model for urban water planning in Phoenix, Arizona, USA. Environ. Plann. Plann. Des. 38, 197–215.
Government of Alberta, 2015. Population Projection, Alberta 2015-2041, p. 12. http://www.finance.alberta.ca/aboutalberta/population-projections/2015-2041-alberta-population-projections.pdf (accessed June 2016).
Grafton, R.Q., Ward, M.B., To, H., Kompas, T., 2011. Determinants of residential water consumption: evidence and analysis from a 10-country household survey. Water Resour. Res. 47 https://doi.org/10.1029/2010WR009685. W08537.
Haque, M.M., Rahman, A., Hagare, D., Kibria, G., 2014. Probabilistic water demand forecasting using projected climatic data for Blue Mountains water supply system in Australia. Water Resour. Manag. 28, 1959–1971.
Headwater Communications, 2007. Water Efficiency Plan 30-in-30, by 2033. City of Calgary Water Resources, Calgary, AB. http://www.calgary.ca/UEP/Water/Documents/Water-Documents/water_efficiency_plan.pdf (accessed June 2016).
House-Peters, L.A., Chang, H., 2011. Urban water demand modeling: review of concepts, methods, and organizing principles. Water Resour. Res. 47 https://doi.org/10.1029/2010WR009624. W05401.
Hussien, W.A., Memon, F.A., Savic, D.A., 2017. An integrated model to evaluate water-energy-food nexus at a household scale. Environ. Model. Software 93, 366–380.
Hussien, W.A., Memon, F.A., Savic, D.A., 2016. Assessing and modelling the influence of household characteristics on per capita water consumption. Water Resources Management 30, 2931–2955.
Inam, A., Adamowski, J., Halbe, J., Prasher, S., 2015. Using causal loop diagrams for the initialization of stakeholder engagement in soil salinity management in agricultural watersheds in developing countries: a case study in the Rechna Doab watershed, Pakistan. J. Environ. Manag. 152 (Suppl. C), 251–267.
Jiang, R.G., Gan, T.Y., Xie, J.C., Wang, N., Kuo, C.C., 2015. Historical and potential changes of precipitation and temperature of Alberta subjected to climate change impact: 1900–2100. Theor. Appl. Climatol. 127, 725–739.
Jorgensen, B., Graymore, M., O'toole, K., 2009. Household water use behavior: an integrated model. J. Environ. Manag. 91, 227–236.
Lowes, 2017. To grey or not to grey: an introduction to greywater systems (accessed April 2017). https://www.lowes.ca/articles/to-grey-or-not-to-grey-an-introduction-to-greywater-systems_a835.html.
March, H., Saurí, D., 2009. What lies behind domestic water use? A review essay on the drivers of domestic water consumption. Boletín de la A.G.E 50, 297–314.
Mays, L.W., 2002. Urban Water Supply Handbook. Chapter 8 in Regional Water Supply Planning and Capacity Expansion Models. McGraw-Hill.
Mayer, P.M., Deoreo, W.B., Opitz, E.M., Kiefer, J.C., Davis, W.Y., Dziegielewski, B., Nelson, J.O., 1999. Residential End Uses of Water. AWWA Research Foundation and American Water Works Association, Denver, CO.
McDonald, R.I., Green, P., Balk, D., Fekete, B.M., Revenga, C., Todd, M., Montgomery, M., 2011. Urban growth, climate change, and freshwater availability. Proceedings of the National Academy of Sciences 108, 6312–6317.
Mirchi, A., Madani, K., Watkins, D., Ahmad, S., 2012. Synthesis of system dynamics tools for holistic conceptualization of water resources problems. Water Resources Management 26, 2421–2442.
Mouatadid, S., Adamowski, J., 2017. Using extreme learning machines for short-term urban water demand forecasting. Urban Water J. 14, 630–638.
Natural Resources Canada, 2007. Municipal Case Studies: Climate Change and the Planning Process. Canadian Institute of Planners, p. 12. https://www.cip-icu.ca/Files/Resources/calgary_en.aspx (accessed June 2016).
NOAA, 2016. The recent global surface warming hiatus. https://www.ncdc.noaa.gov/news/recent-global-surface-warming-hiatus (accessed October 2016).
Olmstead, S.M., Stavins, R.N., 2009. Comparing price and non-price approaches to urban water conservation. Water Resour. Res. 45 https://doi.org/10.1029/2008WR007227. W04301.
Pacific Institute & NRDC, 2014. Urban Water Conservation and Efficiency Potential in California, p. 10. http://pacinst.org/app/uploads/2014/06/ca-water-urban.pdf (accessed October 2016).
Padowski, J.C., Jawitz, J.W., 2012. Water availability and vulnerability of 225 large cities in the United States. Water Resour. Res. 48 https://doi.org/10.1029/2012WR012335. W12529.
Palazzo, J., Liu, O.R., Stillinger, T., Song, R., Wang, Y., Hiroyasu, E.H.T., Zenteno, J., Anderson, S., Tague, C., 2017. Urban responses to restrictive conservation policy during drought. Water Resour. Res. 53 (5) https://doi.org/10.1002/2016WR020136.
Paton, F.L., Maier, H.R., Dandy, G.C., 2013. Relative magnitudes of sources of uncertainty in assessing climate change impacts on water supply security for the southern Adelaide water supply system. Water Resour. Res. 49, 1643–1667. https://doi.org/10.1002/wrcr.20153.
Percy, D., 2005. Responding to water scarcity in Western Canada. Tex. Law Rev. 83, 2091–2107.
Province of Alberta, 2007. Bow, Oldman and South Saskatchewan River Basin Water Allocation Order. Alberta Regulation 171/2007, Water Act.
Qaiser, K., Ahmad, S., Johnson, W., Batista, J., 2011. Evaluating the impact of water conservation on fate of outdoor water use: a study in an arid region. J. Environ. Manag. 92, 2061–2068.
Qi, C., Chang, N.B., 2011. System dynamics modeling for municipal water demand estimation in an urban region under uncertain economic impacts. J. Environ. Manag. 92, 1628–1641.
Rehan, R., Knight, M.A., Haas, C.T., Unger, A.J., 2011. Application of system dynamics for developing financially self-sustaining management policies for water and wastewater systems. Water Res. 45, 4737–4750.
Rogers, E.M., 1995. Diffusion of innovations. Chapter 7 Innovativeness and Adopter Categories, fourth ed. Free Press, New York.
Rood, S.B., Foster, S.G., Hillman, E.J., Luek, A., Zanewich, K.P., 2016. Flood moderation: declining peak flows along some Rocky Mountain rivers and the underlying mechanism. J. Hydrol. 536, 174–182.
Savic, D., Morley, M., Khoury, M., 2016. Serious gaming for water systems planning and management. Water 8, 456.
Scalzitti, J., Strong, C., Kochanski, A., 2016. Climate change impact on the roles of

temperature and precipitation in Western U.S. snowpack variability. Geophys. Res. Lett. 43, 5361–5369. https://doi.org/10.1002/2016GL068798.
Sønderlund, A.L., Smith, J.R., Hutton, C.J., Kapelan, Z., Savic, D., 2016. Effectiveness of smart meter-based consumption feedback in curbing household water use: knowns and unknowns. J. Water Resour. Plann. Manag. 142, 04016060.
Sovocool, K.A., 2005. Xeriscape conversion study final report. Southern Nevada Water Authority, p. 97. http://www.allianceforwaterefficiency.org/WorkArea/DownloadAsset.aspx?id=1248 (accessed October 2016).
Stave, K.A., 2003. A system dynamics model to facilitate public understanding of water management options in Las Vegas, Nevada. J. Environ. Manag. 67, 303–313.
Statistics Canada, 1977. 1976 census of Canada, Census Divisions and Subdivisions, Western Provinces and the Territories. Volume I Population, Geographic Distributions. Canada, Ottawa.
Statistics Canada, 2016. Population of census metropolitan areas. http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/demo05a-eng.htm (accessed November 2016).
Sterman, J.D., 2000. Business Dynamics, Systems Thinking and Modeling for a Complex World. McGraw-Hill, Boston, MA.
Tanaka, S.K., Zhu, T., Lund, J.R., Howitt, R.E., Jenkins, M.W., Pulido, M.A., Tauber, M., Ritzema, R.S., Ferreira, I.C., 2006. Climate warming and water management adaptation for California. Climatic Change 76, 361–387.
Tanzeeba, S., Gan, T.Y., 2012. Potential impact of climate change on the water availability of South Saskatchewan River Basin. Climatic Change 112, 355–386.
Turner, A., White, S., Bickford, G., 2007. The Canberra least cost planning case study. Water Sci. Technol. Water Supply 5, 257–263.
Wang, K., Davies, E.G., 2015. A water resources simulation gaming model for the Invitational Drought Tournament. J. Environ. Manag. 160, 167–183.
Williams, A., Lansey, K., Washburne, J., 2009. A dynamic simulation based water resources education tool. J. Environ. Manag. 90, 471–482.
Winz, I., Brierley, G., Trowsdale, S., 2009. The use of system dynamics simulation in water resources management. Water Resources Management 23, 1301–1323.
Yigzaw, W., Hossain, F., 2016. Water sustainability of large cities in the United States from the perspectives of population increase, anthropogenic activities, and climate change. Earth's Future 4, 603–617.
Yung, B.B., Tolson, B.A., Burn, D.H., 2011. Risk assessment of a water supply system under climate variability: a stochastic approach. Can. J. Civ. Eng. 38, 252–262.